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Assessing the Effects of Trade-induced Technology Imitation on Economic Growth in Africa

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Abstract

The study aims at quantifying the effects of trade-induced technology imitation (proxied by the share of imports in the "easy imitation" SITC category) on economic growth in Africa, using a production function approach in a panel system-GMM estimator. Indicators of trade-induced technology imitation have been built on the Standard International Trade Classification (SITC) using raw data from the United Nations' COMTRADE Statistics. Findings suggest that economic growth tends to be greater in countries with higher ratios of technology imitation, since technology imitation requires creative effort on the part of a firm's employees and will consequently develop capabilities such as skills and efficiency. Another finding is that the lower the level of GDP per capita, the higher the growth effects of technology imitation relative to other forms of technology progress.

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1. Introduction

Economic theories and development experiences alike show that economies that have successfully caught up with the advanced economies have typically gone through a process of significant technology progress. Although researchers are increasingly sensitive to the importance of appropriate policies in support of technological progress, views differ on what constitutes appropriate technology policy, which is particularly daunting for developing economies where research and development (R&D) is relatively scarce (Hausmann and Rodrik, 2003). As an

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alternative to R&D, numerous studies look at spillovers from foreign-direct investment (FDI) as the instrument of technology diffusion (Coe and Helpman, 1995; Coe, Helpman, and Hoffmaister, 1997; Keller, 1998). Other studies consider the possible link between certain types of imports and technological diffusion (Eaton and Kortum, 1996; Keller, 2001). Notably, recent development experiences in Asia suggest that initially countries have frequently relied on successful imitation of foreign technologies to achieve indigenous technological development (Carolan et al., 1998). Before proceeding further, it should be noted that imitation as defined here comprises both "replica" (imitation by legal means, through licenses obtained from the pioneer, or informal imitation, through copying of old and unprotected technologies) and "mimicry" produced through reverse engineering (Ulhoi, 2012).

The economic reasons for the high intensity of imitation are covered already in Poyago-Theotoky (1998). In particular, in developing countries, funding innovation is often out of reach for most local firms. Then, firms reap the benefits of innovation through easy imitation via international trade or other forms of international spillovers. However, despite the central role imitation has played in development and technology catching-up, it has received only modest attention in explanations of economic growth (Niosi, 2012).

Even more worrisome, little empirical research exists on the extent to which such imitation has occurred via trade and how this affects economic growth (Datta and Mohtadi, 2006). The lack of empirical research on this critical issue stems from measurement and data constraints associated with the concept and practice of imitation. Although some of these constraints may still remain, recent progress in international trade statistics (e.g., United Nations' COMTRADE Statistics) has made it possible to mine the data and come up with acceptable proxy indicators for developing countries.

Taking advantage of the advances in trade statistics for African economies, this research aims to quantity the growth effects of trade-induced technology imitation across African countries. To do this, we built a trade-induced imitation indicator and includes it in an augmented growth model that follows Connolly (1997). This model is then empirically tested using a Panel System-Generalized Method of Moment, GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998).

Findings suggest that economic growth tends to be greater in countries with higher ratios of technology imitation, since technology imitation requires creative effort on the part of a firm's employees and will consequently develop capabilities such as skills and efficiency. Another finding is that the lower the level of GDP per capita, the higher the growth effects of technology imitation (proxied by the share of imports in the "easy imitation" SITC category) relative to other forms of technology progress.

The rest of the paper is organized as follow. The next two sections covers respectively methodological and data considerations. Section 4 introduces empirical results while the last section concludes.

2. Methodology

The reference model follows an augmented growth model of Connolly (1997). The empirical estimation proceeded with a panel data. The use of panel data to investigate the growth-effect of trade or technology progress is a common trend in recent years. In this study, we specifically use the Generalized-Method-of-Moment (GMM) system estimator suggested by Arellano and Bover (1995) and later developed by Blundell and Bond (1998), and Blundell et al. (2000). This estimator has the potential advantages of minimizing the bias resulting from estimating dynamic panel models, exploiting the dynamic and time series properties of the data, controlling for the unobserved country-specific effects, and correcting for the bias resulting from the possible endogeneity of the explanatory variables. Consider the following model,

$$y_{i,t} = \delta y_{i,t-1} + X_{it}\beta + \alpha_i + u_{i,t} \tag{1}$$
$$E(\alpha_i) = E(u_{it}) = E(\alpha_i u_{it}) = 0$$

where y is the reported economic growth of country i in year t, X includes all other explanatory variables, α_i is the country-specific unobserved heterogeneity that varies across countries but not over time for each country, and $u_{i,t}$ is the idiosyncratic error term, varying by country and over time. The country-specific unobserved heterogeneity is allowed to be correlated with the explanatory variables. The idiosyncratic error term may also be correlated with some of the explanatory variables.

One problem with estimating equation (1) via OLS is the endogeneity of the lag of the economic growth. If a country in Africa experiences a large positive growth shock for a reason not modeled, the shock is subsumed into the error term. The country-specific unobserved heterogeneity will appear larger over the time span of the data (since it does not vary be year), and in the following year the lag of the economic growth will also be large and positive. This positive correlation between the error term and the lag of the economic growth would yield inconsistent and biased OLS results, results that are in this case biased upwards.

An initial attempt to purge the fixed effects might be panel data fixed effects estimation or least squared dummy variable regression (entering a dummy variable for each country). Roodman (2006) shows that this will not entirely remove "dynamic panel bias" and in fact would result in downward bias on the lag of the economic growth in our previous example. Thus, the magnitude of the estimated coefficient on the lag of the economic growth resulting from an improved estimation strategy should fall between those of the OLS and fixed effects.

One strategy to purge the unobserved heterogeneity is to difference the data. Equation 1, when first-differenced, yields the following:

$$y_{i,t} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (X_{it} - X_{i,t-1})\beta + (u_{i,t} - u_{i,t-1}) \tag{2}$$

or

$$\Delta y_{i,t} = \delta \Delta y_{i,t-1} + \Delta X_{it}\beta + \Delta u_{i,t}$$

The differencing eliminates the country-specific unobserved heterogeneity. However, the lag of the economic growth remains endogenous because $y_{i,t-1}$ is correlated with $u_{i,t-1}$. Other explanatory variables may also be correlated with the lag of the error term if they are not strictly exogenous and only contemporaneously exogenous in the non-differenced equation. Fortunately, deeper lags of the explanatory variables are exogenous and can be used as instruments.
As Roodman (2006) explains, the first-differenced transformation is best used for strongly balanced panels. In an unbalanced panel, if $y_{i,t}$ is missing, then $\Delta y_{i,t}$ and $\Delta y_{i,t+1}$ will be missing. Since our data are unbalanced (in a given year, a number of countries have missing data), we use a second option for purging the unobserved heterogeneity. This method, called "orthogonal deviation" (Arellano and Bover, 1995), subtracts from $y_{i,t}$ the mean of all future available values. This method mitigates data loss and makes all lagged variables available as instruments. We will denote data transformed by orthogonal deviation as:

$$\tilde{y}_{i,t} = \delta\tilde{y}_{i,t-1} + \tilde{X}_{it}\beta + \tilde{u}_{i,t} \tag{3}$$

The dynamic panel *system* GMM estimator employed here incorporates equation (1) in "orthogonal deviations" *and* in levels as a system to increase efficiency. For the level regression, since the unobserved heterogeneity is not purged, instruments must be used. The instruments are the lagged differences of the endogenous explanatory variables. This is based on the assumption that, while the unobserved heterogeneity may be correlated with the levels of the explanatory variables, it will not be correlated with their differences. The following moment conditions are satisfied for the second part of the system (the regression in levels):

$$E[(y_{i,t-1} - y_{i,t-2})(\alpha_i + u_{i,t})] = 0 \tag{4}$$

$$E[(X_{i,t-1} - X_{i,t-2})(\alpha_i + u_{i,t})] = 0 \tag{5}$$

The four moment conditions (equations 3-5) are used to implement dynamic panel system GMM estimation, producing consistent parameters.

3. Data considerations

The datasets for our key variable (technology imitation) have been built from raw data extracted from the United Nations' COMTRADE (2015), 5-digit codes SITC (United Nations' Standard International Trade Classification) for imports. The intuition is that, initially, less-developed countries reduce the technology gap through import-embedded technology and then proceed to imitation (Jovanovic and MacDonal, 1994). It follows thus that technology progress in developing countries proceeds alongside trade flows. Hence, the starting point in measuring such spillover effects would be to consider imports of goods in technology-intensive category; that is Classes 5, 7, 86, and 89 in SITC (Revision 4). These classes include machinery and transport equipment, instruments (optical, medical and photographic), watches, clocks, and miscellaneous manufactured goods (such as office equipment, which in later years has included computers). The concern with this category of items is that these commodity classes include high-technology goods, and thus are not likely to be imitable in low-income countries such as those in Africa. Therefore, following the classification in (Yilmaz, 2002), we restricted the above classes of commodities to low-technology intensive items, which comprise classes in SITC Rev. 3: 51, 52, 54.1, 58, 59, and 75 (for further information, see Yilmaz, 2002) and built our first proxy of technology imitation (Imitation1).

While our first proxy of technology imitation is built from imports of the above-described import classes, it does not necessarily indicate that a country is actually succeeding in bridging its technological gap. To indirectly assess how much of a country is increasing its share of technology intensive exports, our second proxy of technology imitation (Imitation2) relies on exports of the same category as those used in Imitation1. It is worth noting that the basic intuition behind our two measures of Imitation is straightforward. That is the higher the intensity of technology in intra-industrial trade between two countries, the higher the probability that industries in the country with less technological knowledge converges to the country with more technological knowledge.

The datasets comprise times series data for 44 sub-Saharan African countries and sourced as indicated in Table 1. Regression-wise, the dependent variable is GDP per capita growth rate, defined as "the sum of the gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products" (World Bank, 2014). Following Barro (1997), the benchmark model will include the following independent and control variables: physical capital investment (defined as "real gross domestic investment (private and public) as a percentage of GDP"), secondary school enrollment and population growth.

Moreover, two additional variables must be considered in order to control for other factors that could potentially lead to spurious correlation between the independent variables and the research proxies. For example, a finding that trade-induced imitation contributes positively to economic growth could simply reflect an openness effect, rather than spillovers from imitation. For this reason, an openness measure will also be included in the research regressions. Similarly, since innovation performance affects the domestic imitation environment, an innovation index is included in the regressions.

Table 1. Standard growth's control variables (Barro, 1997)

Variables	Sources
1- Real GDP per capita in constant dollars of 2005.	Summers and Heston (7.1) and missing data from (Global Development Finance & World Development Indicators).
2- Investment	Summers and Heston (7.1) and missing data from Global Development Finance & World Development Indicators.
3- Trade openness	World Development Indicators 2014, CD-R. World Bank.
4- Education index	World Development Indicators 2014, CD-R. World Bank.
5- Imitation1	UN's COMTRADE Database, raw data source
5- Imitation2	UN's COMTRADE Database, raw data source
7- Population	World Development Indicators 2014, CD-R. World Bank.
8-Infrastructure index.	World Development Indicators 2014, CD-R. World Bank.
9-Innovation index	World Development Indicators 2014, CD-R. World Bank.

4. Empirical results

A central issue before making the appropriate econometrics specification, is to test the stationarity or unit root requirement. This is done by following the approach of Im, Pesaran, and Shin (IPS) (1995) who developed a panel unit root test for the joint null hypothesis that every time series in the panel is non stationary. Results of this test are not reported (available upon request) but in every case we reject a unit root in favor of stationarity (the results were also confirmed by the Fisher-ADF and Fisher-PP panel unit root tests) at the 5 percent significance level and it was deemed safe to continue with the System GMM estimation.

Estimation results of the System-GMM are presented in Table 2. Looking at the benchmark model (Column 1), the control variables of the augmented growth model maintain their expected influence and all test statistics confirm the validity of our instruments. Also, the investment rate as a share of GDP has a positive and highly significant coefficient. Increases in population growth have a significantly negative effect on GDP per capita growth rates and the influence of investment in human capital (Education) is positive and significant at the conventional 10 per cent level.

Expectedly, the coefficient of innovation index remains not significant both in the benchmark model as well as the specification that include technology imitation. Hence, dropping Innovation in the subsequent models improved efficiency of the estimation results.

All realizations of the potentially endogenous explanatory variables lagged by two periods and more have been included as instruments and the Sargan/Hansen test of overidentifying restrictions confirms the joint validity of our instruments. The p-value of the Arellano-Bond test for second-order correlation in differences (Ar(2) Test) rejects first-order serial correlation in levels. Having established a valid benchmark, we subsequently include our main variable of interest: technology imitation in three variants (*Imitation1*, its lagged value and *Imitation2*).

Including our alternative measures of technology imitation, *Imitation1* or its lagged value (*Imitation1* (t-1(), fundamentally changes the regression results for the impact of investment on GDP per capita growth (columns 2-6). Especially, the coefficient of investment increased from 0.106 in the benchmark model to over 0.150 in subsequent models. Importantly, *Imitation1* (t-1) has a positive coefficient and is significant at the 5 per cent level of confidence. At the same time, the coefficient of *Imitation1* is not only significant at the conventional 1 per cent level but also of higher magnitude than *Imitation1*. This language can be interpreted to mean that an increase in the volume of easy imitation items divided by total imports of the previous period by one unit at the mean is associated with an increase in GDP per capita growth of 0.106 percentage points over the next period.

Surprisingly, contrary to *Imitation1*, results reported in Column 4 suggest that the coefficient for *Imitation2* (proxy by exported classes defined above) is not significant and thus the variable has no impact on economic growth. It might be argued that for African countries the preconditions for the realization of a positive technology intensive exports-income-growth nexus are not being achieved yet.

The evidence established so far has been for the total sample, including both middle-income countries such as South-Africa or Mauritius and LICs (Low Income countries; based on World Bank's classification) such as Malawi or the DRC. The question arises if the positive influence of trade on income growth is robust for a sample of LICs only. Columns 5-6 shed some light on this issue by showing the results for a subsample of 22 African countries classified as LICs. As it can be seen from Columns 5-6, the coefficients of Imitation1 and *Imitation(t-1)* are even higher and significant at the conventional 1 and 5 per cent level. This suggests that the lower the level of GDP per capita, the higher the growth effects of technology imitation (proxied by the share of imports in the "easy imitation" SITC category) relative to other forms of technology progress.

Table 2. Panel System-GMM Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)
Gdp (t-1)	-0.0597***	-0.0466**	-0.674***	-0.067**	-0.0477*	-0.0542*
	(-2.638)	(-2.320)		(-2.274)	(-1.666)	(-1.780)
Investment ratio	0.107***	0.185***	0.181***	0.164**	0.209***	0.174***
	(5.402)	(5.946)		(2.047)	(4.170)	(4.138)
Population growth	-0.331***	-0.253**	-0.482***	-0.394	-0.219	-0.291
	(-2.878)	(-2.065)		(-1.083)	(-1.568)	(-1.643)
education	0.0669*	0.0583	0.0704*	0.064*	0.0531*	0.0723
	(1.755)	(0.0586)	(1.930)	(1.821)	(1.904)	(1.321)
Innovation	0.0624					
	(1.226)					
Imitation1		0.0226*			1.143***	
		(1.701)			(4.064)	
Imitation1(t-1)			0.1065**			1.382***
			(2.571)			(4.069)

Imitation2				0.0631 (1.268)		
Observations	758	758	709			
Number of countries	44	44	44	44	22	22
			Specification tests			
Sargan/Hansen	0.353	0.21	0.405		0.575	0.764
Ar(2) Test, p-value	0.592	0.62	0.768		0.668	0.487

Notes: **significant at 10% level; ** significant at 5% level; *** significant at 1% level; t-values reported in parentheses; constant term and time dummies always included but not reported.
Ar(2) Test refers to the Arellano-Bond test for second-order correlation in differences; Sargan/Hansen test of overidentifying restrictions.

Finally, one might wonder why the estimates for import coefficient from imitation (Columns 2-6) and innovation index (Column 1) are substantially different. This may suggest that for technology progress, African firms are more dependent on imported inputs rather than doing their own R&D activities.

These finding corroborates the idea that initially developing countries reduce the technology gap through import-embedded technology and then proceed to other forms of imitation to achieve indigenous technological development ((Jovanovic and MacDonal, 1994; Carolan et al., 1998). Overall, the findings of this study are consistent with endogenous growth theories, which consider “learning by importing” as an important channel of technology and economic growth.

5. Conclusion

The study aimed at assessing the effects of trade-induced technology imitation on economic growth in Africa a production function approach in a panel GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995). Overall, the results support the view that certain forms of technology imitation (such as imported low-technology intensive items) has a positive and significant effect on growth for the sample of African economies under study. In other words, economic growth tends to be greater in countries with higher ratios of technology imitation, since technology imitation requires creative effort on the part of a firm’s employees and will consequently develop capabilities such as skills and efficiency.

Combining these results, we may conclude that intermediate inputs may enhance productivity by providing domestic firms in Africa with access to technologies that are embodied in foreign capital goods that are not available domestically. Hence, African policymakers can foster technology progress by focusing on tax-incentives designed to encourage local firms to engage in imports of technology-intensive parts and components as inputs in their production processes.

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